Modeling, Combining and Discounting Mine Detection Sensors within Dempster-Shafer Framework

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ABSTRACT

In this paper, ideas for modeling humanitarian mine detection sensors and their combination within Dempster-Shafer framework are presented. Reasons for choosing this framework are pointed out, taking into account specificity and sensitivity of the problem. This work is done in the scope of the HUDEM* project, where three promising and complementary sensors are investigated, so detail analysis is performed in case of fusing the data from them. A way for including in the model influence of various factors on sensors and their results is discussed as well and will be further analyzed in the future. The application of the approach proposed in this paper is illustrated on the case of sensing metallic objects, but it is possible to modify it for other situations.

Keywords: humanitarian mine detection, sensor modeling, fusion, Dempster-Shafer method, discounting factors

1. INTRODUCTION

Unfortunately, there is no single sensor used in the field of humanitarian demining that can reach necessarily high detection rate in all possible scenarios where mines can be found. A sensor that works well in one scenario, for one type of soil, moisture, temperature, burial depth, mine material, size, shape, fails to detect mines in a different scenario. Therefore, a lot of effort has been made in order to take the best from several complementary sensors. One of the most promising combinations in that sense is: an imaging metal detector (MD), a ground penetrating radar (GPR) and an infrared camera (IR); that is the set of mine detectors analyzed in this paper.

Since reliability and detection capabilities of sensors are strongly scenario dependent, it is very important to characterize each of the sensors that are combined. In other words, ways for modeling influence of various factors on sensors and their results, as well as on results of combination have to be investigated in detail, in order to reach fusion results that would be as good as possible for some concrete scenario.

Now, which fusion method to use in order to obtain such good results? There is no universal approach and its choice should strongly depend on the problem itself.[1,2] It should be pointed out that in this domain of application, we have to deal with following information:

- the data are basically numerical (images, sensor measurements);
- they are not numerous enough to allow reliable statistical learning (as shown through our previous work[3]);
- they are highly variable depending on the context and conditions;
- they do not give precise information on the type of mine (ambiguity between several types);
- not every possible object can be modeled (neither mines nor objects that could be confused with them).

*HUDEM (HUmanitarian DEMining) is a technology exploration project on humanitarian demining launched by the Belgian Minister of Defense with funding provided by his Department, the Ministry of Foreign Affairs and the State Secretariat for Development Aid.

That is why we propose a method based on belief functions in the framework of Dempster-Shafer (DS) theory,[4,5] since in this framework, ignorance, partial knowledge, uncertainty and ambiguity can be appropriately modeled. This method has been suggested in Ref. 6,7, but it is more detailed and developed here.

The main motivation for exploring possibilities of modeling mine detection system in DS framework is to be easily able to include and model existing knowledge regarding:

- the three mine detection sensors under analysis (e.g. detection of IR is limited to several centimeters below the soil surface in the best case, standard GPR cannot detect surface-laid and shallowly buried objects, MD can detect just objects containing metal, etc.),
- some known mine laying principles (e.g. antipersonnel landmines are usually buried on the depths up to 25-30 cm, rarely deeper),
- mines themselves (e.g. majority of currently laid mines around the world is highly metallic, with circular top surface, appearing elliptical in images of these three sensors in general case because of some burial angle, etc.),
- objects that each of these sensors can easily confuse with mines (e.g. stones of adequate size and shape for IR and GPR sensor, metallic cans for MD, etc.),

Also, there has to be a way to allow a deminer to express his opinion about usefulness of each of the sensors within some concrete scenario. It must not be forgotten that his life, knowledge and experience are precious.

Another aspect of our ideas should be mentioned too. We believe that the approach of combining sensors should improve detection results, but that it is not possible to reach the highest possible level of detection, simply because it is not possible to predict everything in all the real situations where mines can be found. Because of that, our idea is to give to a deminer as much information as possible, starting from processed data of separate sensors up to a final conclusion, but the ultimate decision has to be left to the deminer. Therefore, the result of this DS model should be an ordered list of guesses what a currently observed object could be, together with confidence in these results.

It also has to be pointed out that, at least for these three sensors, there is no criterion by which it is possible to say that if it is fulfilled, the object is a mine. It can be just the opposite, i.e. to have a criterion that can tell us when an object is (most possibly) not a mine. Consequently, our results tell how expectable is that an object is not a mine, or that it is either a mine or something else. Although it may sound as a drawback of the method, we have to remember that mines should not be missed, so detecting that something is not a mine and that it is a mine or something else seems to be the safest approach in this complex problem.

In the following, on the basis of the characteristics of imaging MD, GPR and IR sensors from the point of view of mine detection, as well as on the basis of the general ideas for applying the DS approach, explained above, the appropriate choice of criteria and of respective mass assignment for each of the sensors will be discussed, in the case that an object under observation is metallic. Also, preliminary ideas for including in the model the influence of the concrete scenario, i.e. confidence of sensors in their assessments, importance of each criterion as well as deminer's confidence in each of the sensors will be presented, based on the idea of introducing discounting factors.[4,8,9] First, promising results will be given, and potential problems, linked to the sensitivity of the problem itself, will be pointed out. Finally, ways for estimating confidence degrees will be presented.

2. CHOICE OF CRITERIA AND MODELING THE RESULTING MASSES

The most often case in mine detection reality is when all three analyzed sensors give an alarm, and the response of a MD is strong, meaning that the object has a high metallic content. That is the first case we decide to analyze and model in this framework, as it should be a good basis for modifications and generalization to the other cases.

All three sensors give images, i.e. information about the shape and size of an object. Since a large number of mines has elliptical top surface[†] (circular, but becomes elliptical when seen under some burial angle), if the sensors are (equally) reliable and if a MD claims that the object is highly metallic, the following classes of objects can exist, that create the frame of discernment Θ:

[†]In the following, the term "regular" will be used.

- MR (metallic mine of regular shape),
- MI (metallic mine of irregular shape),
- FR (friendly, i.e. non-dangerous object of regular shape) and
- FI (friendly object of irregular shape).

The criteria that could give us the most information about some subsets of Θ are the following ones:

- for each of the three sensors:

1. shape ellipticity (how well the shape fits in an ellipse); it assigns masses to subset with regular shapes, with irregular shapes and to full set, i.e. to {MR, FR}, {MI, FI}, Θ;
2. shape elongation, giving masses to subsets {MR, FR}, {MI, FI}, Θ;
3. area/size; since we know which range of mine sizes exists, if the size is within that range, it can be anything, assigning masses to Θ, but if it is out of that range, mass should be given to {FR, FI};

- for MD: burial depth; again, it is known on which depths mines can be expected, so, similarly to the area criterion, masses are assigned to {FR, FI} and Θ;
- for GPR:

1. depth dimension (i.e. height) of the object, giving, as for burial depth and for area, information about masses of {FR, FI} and Θ;
2. comparison of the position of the metallic object detected by MD and the object depth interval detected by GPR, assigning masses to {FR, FI} and Θ. Note that this is an original way to account for links between sensors.

We model all criteria and define mass assignments for each of them according to our knowledge based on literature survey as well as on trials performed within our project. In the following subsections, these models will be briefly explained (more about them can be found in Ref. 7). We expect that they will be verified and tuned in trials planned for this year.

2.1. Ellipse fitting mass assignment

Once an object under investigation is isolated on images of the three sensors, an ellipse fitting algorithm[10,11] is applied on each of them. Mass for the subset of regular shapes assigned by this criterion is smaller value from the two, where one is the percentage of the object area that belongs to the fitted ellipse as well, and the other one is the percentage of the ellipse area that belongs to the object as well, i.e.:

$$m_f\{MR, FR\} = \min\left\{\frac{A_{oe}-5}{A_o}, \frac{A_{oe}-5}{A_e}\right\}, \tag{1}$$

where A_{oe} is the part of object area that belongs to the fitted ellipse as well, $A_o$is the object area, A_e is the ellipse area [‡]. Mass of irregular subset is the larger value from the two, one presenting the percentage of ellipse area that does not belong to the object, the other one presenting the percentage of object area that does not belong to the fitted ellipse:

$$m_f\{MI, FI\} = \max\left\{\frac{A_e - A_{oe}}{A_e}, \frac{A_o - A_{oe}}{A_o}\right\}. \tag{2}$$

Mass of full set is then the remaining mass, i.e.:

$$m_f\{\Theta\} = 1 - m_f\{MR, FR\} - m_f\{MI, FI\}, \tag{3}$$

by which ignorance (i.e. ambiguity) is modeled.

[‡]Factor of 5 is taken to include limit case of an ellipse with just 5 pixels, where we cannot judge about the shape at all, so ignorance should be maximum.

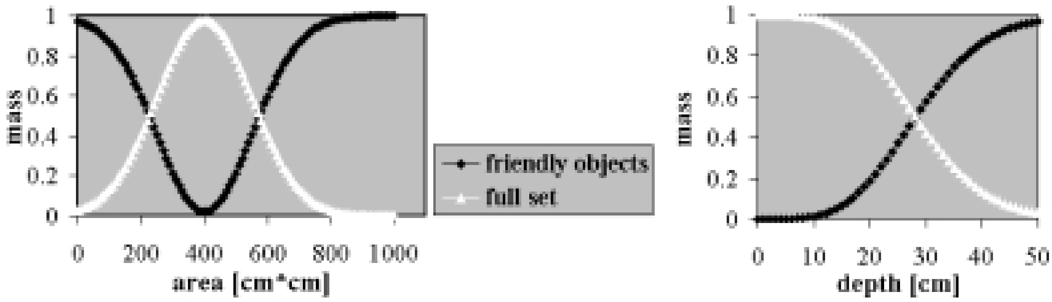

Figure 1. An illustration of: area/size mass assignment (left), depth mass assignment (right)

2.2. Elongation mass assignment

As input, we have again a thresholded image as above. We calculate mass center, and then we find:

- minimum and maximum distance of bordering pixels from the mass center, and the ratio between them ($ratio1$);
- second moments, and from them the ratio of minor and major axis of the obtained quadratic form ($ratio2$).

Mass assignment for regular subset is the smaller of the two ratios:

$$m_e\{MR, FR\} = \min(ratio1, ratio2)\,, \tag{4}$$

while mass of the irregular subset is the absolute value of their difference:

$$m_e\{MI, FI\} = |ratio1 - ratio2|\ . \tag{5}$$

By this, the larger the difference between these two ratios, the smaller the mass for regular shapes, as well as the larger the mass of irregular shapes. Again, full set takes the rest, indicating that the case is not ideal:

$$m_e\{\Theta\} = 1 - \min(ratio1, ratio2) - |ratio1 - ratio2| = 1 - \max(ratio1, ratio2)\,. \tag{6}$$

2.3. Area/size mass assignment

When a preliminary information about expected size of mines exists (e.g. on the basis of the MD response, of knowledge about types of mines laid in some particular region, etc.), a range of areas of detected object that could be a mine, but something else as well, can always be predicted with some tolerance, accounting for possible deformations because of some burial angle. Outside that range, it is much more expectable that objects are friendly. Accordingly, masses are modeled as given in the left side of Fig. 1.

2.4. Burial depth mass assignment

Similarly to expected area/size range of mines, there is a range of burial depths where it is more expectable that mines would be buried - when a MD detects something on these, smaller depths, mass should be assigned to the full set, since it can be either mine or something else. On the contrary, at higher depths, it is much more probable that the detected object is something else but mine. This idea for mass assignment is illustrated in the right side of Fig. 1.

2.5. Depth dimension mass assignment

Once again, some range of depth dimensions or heights (detectable by GPR) of object exists, where it is more expectable that an object is a mine (but it can be something else as well); on the other hand, some too small or too large objects are quite surely non-dangerous. Therefore, our preliminary choice of mass assignments is as shown in the left side of Fig. 2.

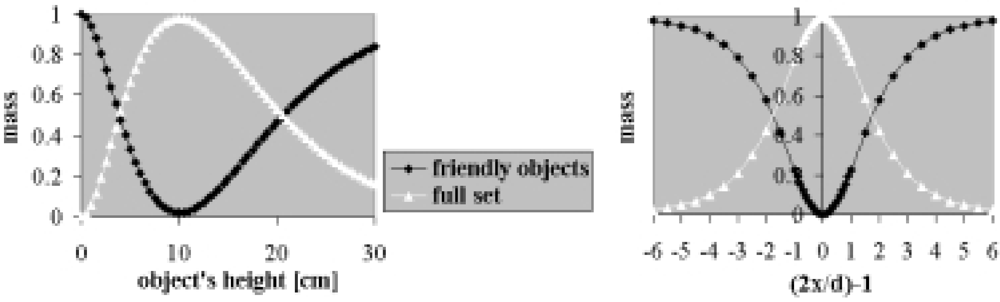

Figure 2. Masses: depth dimension (left), comparison of MD and GPR depth information (right)

2.6. Mass assignment for comparison of GPR and MD depth information

In case of detecting mines, agreement should exist between the depth dimension detected by GPR and depth position of metal detected by MD, i.e. the second one should be within the first interval. If that is the case, the object can be anything from our frame of discernment, but if it is not the case (with some tolerance), the object should not be a mine. This idea for mass assignments is illustrated in the right side of Fig. 2, where x is the depth position detected by MD, measured from the top level detected by GPR, and d is the height of the object detected by GPR (so, the maximum value is given to the mass of full set when the position of metal detected by MD is in the middle of the depth interval extracted by GPR, i.e. when $x = d/2$).

3. DISCOUNTING FACTORS

As already stated, behavior of each of the three sensors is strongly scenario-dependent, referring to:

- quality of the acquired data, that influences assessment of sensors when judging about some criterion, importance of each criterion and confidence in that sensor;
- detection ability/reliability of each of the sensors under particular weather conditions, type of soil, etc, that again affects confidence in that sensor;
- types of objects under analysis, influencing importance of each of the criteria.

Because of that, a way should exist to include influence of various factors (environmental conditions, data quality, etc.) on the obtained results; since it would be very difficult to model individually each environmental factor and its influence, we propose to include them in one discounting factor. Additionally, as pointed out previously, a deminer should have a possibility to give his own opinion about reliability of each of the sensors within a concrete scenario, i.e. his confidence in each of them. Finally, depending on a concrete situation, some criteria could become more important (and reliable), others less. These are main reasons for including discounting factors[4,8,9] in our model.

Discounting factors, d_{ij}, consist of three types of parameters:

- g_{ij} - confidence level of sensor j in its assessment when judging criterion i (0 - not confident at all, 1 - completely confident);
- b_i - level of importance of criterion i (1 - very low, 3 - very high);
- s_j - deminer's confidence into sensor j's opinion,

where $i \in \{a, c, d, e, f, h\}$, $j \in \{G, I, M\}$, with: a - area, c - comparison of depth information from MD and GPR, d - depth, e - elongation, f - ellipse fitting, h - depth dimension of an object, G - GPR, I - IR, M - MD.

3.1. First ideas for calculating g_{ij}

3.1.1. Area/size for IR and GPR, i.e. g_{aI} and g_{aG}

We define level g_{aI} (confidence of IR in its assessment when judging the area criterion) as a function of agreement in area between IR and MD. Namely, in one of the starting steps, we decide on the basis of the strength of signal of MD (or/and the area detected by it) which case to further analyze. It means that, before this moment, we already decided that we analyze the case of high metal content (i.e. metallic) object. What is also done before this moment is that, since IR does not give information about distance from it and the observed object, the area extracted by this sensor is estimated on the basis of the depth information extracted by MD (or by GPR). At this point, we can have two cases:

- (area detected by MD) $\approx$ (area detected by IR); in ideal case of a high metal content object these two areas would be equal, but this equality is understood with some allowed estimated tolerance because of two reasons:
  1. measurements are imprecise, and therefore we cannot expect a strict equality;
  2. IR and MD do not measure the same objects (the same phenomenon);

  in this case, we propose to calculate g_{aI} as:

  $$g_{aI} = \frac{\min(MD\,area, IR\,area)}{\max(MD\,area, IR\,area)}\,; \tag{7}$$

  (so that maximum value of this factor does not exceed 1 in case that area of IR is slightly smaller than the one of MD because of some imprecision);

- otherwise, i.e. areas detected by MD and IR are (quite) different (in either sense); the possibility that it is a low-metal content object was discarded before this point; what remains is that these two sensors do not refer to the same object, so, in the next step, these two areas are compared with area information extracted by the third sensor, GPR; if this area is similar to one of the previous two, then that sensor and GPR are clustered together, and the third one separately, and our analysis "switches" to the case where GPR and that sensor with similar area refer to the same object, while the third one refers to another; if there is no similarity in areas between these three sensors, the case when they all refer to different objects has to be further analyzed.

Calculation of g_{aG} (confidence level of GPR in its assessment when judging area criterion) is performed in the same way: it is compared with MD area, etc.

3.1.2. Ellipse fitting (g_{fI}, g_{fG}, g_{fM})

Confidence of IR sensor in its estimation of masses regarding ellipse fitting criterion is a function of the shape itself (as well as of ellipse fitting criterion and mass assignments) - the larger the mass difference between regular and irregular set, the larger the confidence in the assessment, e.g.:

$$g_{fI} = (m_{fI}\{MR, FR\} - m_{fI}\{MI, FI\})^2\,. \tag{8}$$

Confidence levels for this criterion for the other two sensors are estimated in the same way:

$$g_{fG} = (m_{fG}\{MR, FR\} - m_{fG}\{MI, FI\})^2\,, \tag{9}$$

$$g_{fM} = (m_{fM}\{MR, FR\} - m_{fM}\{MI, FI\})^2\,. \tag{10}$$

3.1.3. Elongation (g_{eI}, g_{eG}, g_{eM})

Similarly to the previous criterion, we define the confidence level in estimation of elongation as function of how well regular and irregular subsets are distinguished by the chosen criterion:

$$g_{eI} = (m_{eI}\{MR, FR\} - m_{eI}\{MI, FI\})^2\,, \tag{11}$$

$$g_{eG} = (m_{eG}\{MR, FR\} - m_{eG}\{MI, FI\})^2\,, \tag{12}$$

$$g_{eM} = (m_{eM}\{MR, FR\} - m_{eM}\{MI, FI\})^2\,. \tag{13}$$

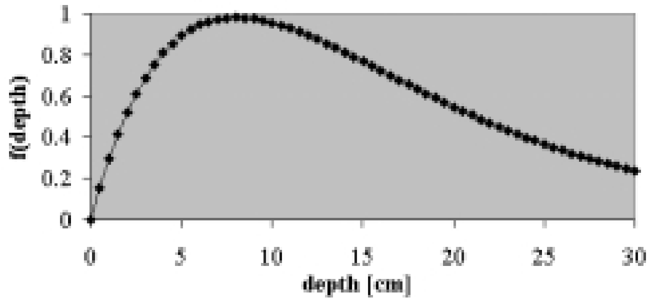

Figure 3. Confidence in GPR in function of depth estimated by MD

3.1.4. Comparison of depth information of GPR and MD (g_{cG})

Here, results of two sensors are compared, without knowing for sure which one is more reliable. Consequently, confidence level of GPR in its assessment regarding this criterion becomes a function of the mass given to a full set, i.e. to how well these two sensors agree - if they are in agreement, we can believe that both sensors are quite reliable and vice versa. Additionally, this confidence depends on the depth information as well; namely, a larger confidence to this comparison is put if the depth is within the range that is detectable by GPR. Therefore, this confidence level is defined as:

$$g_{cG} = m_{cG}\{\Theta\} \cdot f(depth)\,, \tag{14}$$

where function $f(depth)$ has a shape given in Fig. 3.

3.1.5. Burial depth by MD (g_{dM})

As for the previous factor, since it is not known which sensor is more reliable, depth estimation of MD has to be the function of its agreement with GPR:

$$g_{dM} = m_{cG}\{\Theta\}\,. \tag{15}$$

3.1.6. Depth dimension detected by GPR, g_{hG}

This confidence level is defined as a function of the depth information too (as in Fig. 3), since a standard GPR is not reliable neither for surface-laid or shallowly buried object nor for very deeply buried ones (its maximum detection depth strongly depends on moisture level, so it could be later modified to include this information, if we will be able to measure it):

$$g_{hG} = f(depth)\,. \tag{16}$$

3.1.7. Area/size by MD (g_{aM})

We define the confidence of MD in its assessment when judging about area of the object as a function of the strength of the signal, or, of the maximum value of pixels in its image response in comparison to the image scale:

$$g_{aM} = \frac{max\,response}{image\,scale}\,. \tag{17}$$

3.2. How to estimate s_j ?

In general, these coefficients depend on factors that affect reliability of sensors, such as environmental conditions, i.e. time of the day, moisture etc. Since we do not know whether we will have collateral data and which of them, at this moment full confidence is given to a deminer's opinion about reliability of sensors. This confidence will be probably biased by how much the deminer trusts in each of the sensors, either because he is more familiar with some of them than with some others, or because of his personal opinion about reliability of a particular sensor in the current scenario (especially for parameters that are difficult to quantify, e.g. how dense and high the vegetation is, how good the weather is, etc.).

The idea is that a deminer will give, for each of the sensors, numbers describing his belief in reliability of that sensor, where the higher the number, the larger the confidence in that sensor; if two sensors have the same confidence number, that means that the deminer's belief is that they are approximately equally reliable in that scenario. These values he gives have to be rescaled, so he has to provide his scale as well (more about this idea can be found in Ref. 6). Relationship between masses obtained by one scale should not be disturbed by choosing another one (e.g. by another deminer, who prefers different, wider or narrower, scale); it can be expected that indeed this will be preserved, and that is the most important point for further analysis of results, i.e. creating an ordered list of guesses about the true identity of an observed object.

3.3. What about b_i ?

For these coefficients, representing importance of criteria, there are several open possibilities, that will be further investigated in the future work:

- their choice can be again left to a deminer (how important for him is each of the criteria), and this solution is chosen in this paper;
- their values can be preset for each of the predictable cases, i.e. they can depend only on the currently explored case (e.g. metallic object, low-metal content object etc.);
- they can be at the beginning chosen all the same, and after combination of masses, these coefficients can be tuned depending on which subset has the highest mass (e.g. coefficients will be adjusted so that the criteria that give more information about the type of object with the highest mass become more important); then, combination with these modifications can be performed, and if the results are consistent, we can be more confident in them; if not, we can decrease the confidence in the first subset, and perform the same analysis for the subset with the second highest mass, etc.; possibility that this way induces some bias should be investigated as well.

3.4. How to calculate d_{ij} ?

We choose a very simple function of the three types of coefficients discussed above, where each factor can be used in successive discounting, and then the global factor will be a product, such as:

$$d_{ij} = 1 - g_{ij} \cdot (k_1 \cdot s_j + l_1)(k_2 \cdot b_i + l_2)\,, \tag{18}$$

where k_m and l_m, $m = 1, 2$, are coefficients that have to be tuned. That is a serious task that will be done in the future work, through a careful study of their influence, if they are all necessary or not. This will be done not only by comparing resulting discounting factors, but also the influence on resulting masses and decisions. For the beginning, the simplest is to take:

$$l_1 = l_2 = 0\,, \tag{19}$$

$$k_1 = \frac{1}{s_{scale}}\,, \tag{20}$$

$$k_2 = \frac{1}{b_{scale}}\,, \tag{21}$$

i.e. to calculate the global discounting as:

$$d_{ij} = 1 - g_{ij} \cdot \frac{s_j}{s_{scale}} \cdot \frac{b_i}{b_{scale}}\,, \tag{22}$$

where s_{scale} and b_{scale} are scales for s and b parameters, respectively. After gathering the data from all three sensors, we expect that it will be possible to finally adjust all these parameters, as well as previously explained mass assignments per criterion.

Masses assigned for each of the sensors and for each criterion are modified by these coefficients in the following way:

- for some subset $A \neq \Theta$, new masses, $m_{ijNEW}(A)$, are computed from the initial ones, $m_{ij}(A)$, as:

$$m_{ijNEW}(A) = (1 - d_{ij}) \cdot m_{ij}(A)\,; \tag{23}$$

- for full set:

$$m_{ijNEW}(\Theta) = (1 - d_{ij}) \cdot m_{ij}(\Theta) + d_{ij}\,. \tag{24}$$

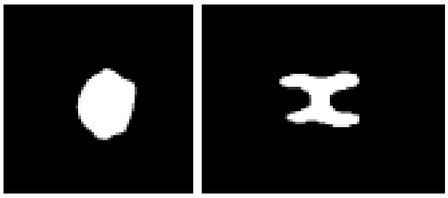

Figure 4. Test images

4. FIRST RESULTS

After calculating and discounting masses for each criterion and for each sensor, we combine them using the well-known DS conjunctive rule[4] in unnormalized form (to keep track of conflict and take it into account in the decision step, as will be shown soon):

$$m(A) = \sum_{\substack{i,\, j \\ A_i \cap B_j = A}} m_1(A_i) \cdot m_2(B_j)\,, \tag{25}$$

where m_1 and m_2 are basic mass assignments, and their focal elements are A_1, A_2, ... A_k and B_1, B_2, ... B_l, respectively.

We analyze four cases; for each of them, obtained (unnormalized) masses are given in Table 1:

- case 1 - an elliptical metallic object given in Fig. 4 is seen approximately equally by all three sensors and it is buried on a depth where mines can be expected, its area is similar to mines, its depth dimension is again as for mines, and MD and GPR agree about its depth position; discounting is not included;
- case 2 - it is similar to the case 1, but with discounting factors, where only factors for confidence levels are included, i.e. it is assumed that all sensors are highly reliable and that all criteria are equally important;
- case 3 - MD and GPR behave as in the previous two cases, i.e. detect some moderately buried object; here, performance of IR sensor is drastically influenced by some factors (e.g. if vegetation is high and dense) that limit its detection to the surface, where it registers some object of the similar area as the object that other two sensors detect, but of the X-shape (as in the right side of Fig. 4); there is no discounting, i.e. a deminer cannot express his doubts about reliability of IR;
- case 4 - discounting is included in the case 3, and a deminer claims that the scale of reliability of sensors is 5, where he gives the highest level of confidence for GPR and MD, but the lowest for IR; importance of all criteria remains equal.

As can be concluded, there is no important change in the results for the cases 1 and 2, indicating that under almost ideal conditions, discounting factors do not influence results to a great extent. On the other hand, the case 3 (i.e. without discounting) has a high degree of conflict between sensors (high value of mass of empty set before normalization), indicating that something is wrong with some of the sensors[§]. If DS rule in normalized form were applied (i.e. masses were divided by (1-m{∅})), this information would have been lost. After discounting (case 4), the value of conflict is significantly suppressed, since the sensor that is not reliable is strongly discarded.

Therefore, even if in some of previous steps it is not noticed that these sensors do not refer to the same object, i.e. they are not clustered in two groups, behavior of the system and, most importantly, final result can be significantly improved by introducing confidence factors and allowing to a deminer a possibility to express his opinion about reliability of each of the sensors.

Several possibilities for interpreting these results exist, depending mainly on the way the subsets containing mines (and some other elements) are treated. We choose the cautious approach, where such subsets are treated as

[§] "Open-world assumption" (something outside the frame of discernment happened, e.g. a sensor is broken or detects something different than others) is justification for keeping masses unnormalized.

Table 1. Resulting masses after combination for four analyzed cases

	Cases			
Masses	case 1	case 2	case 3	case 4
m{FR}	0.0585	0.0558	0.0127	0.04
m{FI}	1.6e-07	9.6e-05	8.8e-06	3.9e-04
m{FR,FI}	1.8e-12	9.5e-05	6.9e-13	5.9e-04
m{MR,FR}	0.9279	0.9015	0.2021	0.845
m{MI,FI}	2.5e-06	0.0017	1.5e-04	0.0666
m{Θ}	2.8e-11	0.0015	1.1e-11	0.009
m{Ø}	0.0135	0.0393	**0.785**	0.0384

a potential danger, i.e. in case of any ambiguity, far more importance is given to mines. Applying such a cautious approach to these four cases, the ordered list of guesses what an object could be becomes, in the simplest form:

- case 1: 1) mine, 2) friendly object, 3) something else;
- case 2: 1) mine, 2) friendly object, 3) something else;
- case 3: 1) something else, 2) mine, 3) friendly object;
- case 4: 1) mine, 2) friendly object, 3) something else.

Another problem is estimation of confidence degrees. We test three ways:

- to calculate belief (Bel) and plausibility (Pl) for each of the classes, and use the interval [Bel, Pl] as a measure of confidence;
- to compare believes and plausibilities of different classes;
- to calculate pignistic probabilities.[12]

Table 2. Belief and plausibility for four analyzed cases

	[Bel(A), Pl(A)]			
A	case 1	case 2	case 3	case 4
{MR,MI}	[0, 0.9407]	[0, 0.9419]	[0, 0.941]	[0, 0.9574]
{FR,FI}	[0.0593, 1]	[0.0581, 1]	[0.059, 1]	[0.0426, 1]

Belief and plausibility of a subset A are[4]:

$$Bel(A) = \sum_{B \subseteq A} m(B)\,, \tag{26}$$

$$Pl(A) = \sum_{B \cap A \neq \emptyset} m(B)\,, \tag{27}$$

i.e. Bel(A) measures the total support provided by evidence towards the truth of A, while Pl(A) is a measure of the degree by which the evidence fails to deny it. Results given in Table 2 illustrate calculated Bel and Pl for cases from Table 1, after normalization of masses (i.e. division by (1-m{Ø})), where two main classes are spotted, i.e. mines and friendly objects. It can be noted that in all four cases ignorance for mines is almost total, so by the cautious approach, we can say that plausibility that an object is a mine in these cases is high, and that this object should be further analyzed as a potential danger.

Now, comparing Bel and Pl for these two main classes, mines and friendly objects, we again see that in all four cases they are very close to each other (and almost maximum), so, being cautious, we would give advantage to possibility that it is a mine.

Calculation of pignistic probabilities is based on equal splitting of a mass assigned to some proposition B among the singleton hypotheses A_i that constitute it,[12] so that final pignistic probability of a singleton hypothesis is the sum of all its split masses, i.e.:

$$P(A_i) = \sum_{A_i \subset B} \frac{1}{|B|} m(B)\,. \tag{28}$$

It is easy to see that, for all four cases, pignistic probabilities of mines and of friendly objects would be very close to each other, so, again, ignorance about true identity is very high and by cautious approach we would surely further analyze this object.

More results of applying these three methods for estimating confidence degrees can be found in Ref. 7, where their real power is illustrated on some other cases. All the obtained results show that our model is promising, i.e. that it behaves in accordance with what can be expected in reality.

5. CONCLUSIONS AND FUTURE WORK

Reasons and ideas for modeling fusion of mine detection sensors within the DS framework are given in this paper, taking into account how sensitive and specific this problem is by nature, since the only goal is to preserve lives of the people from mine infected areas as well as of deminers. The main advantage of this approach is in its possibility of including existing knowledge about the problem. On the basis of this knowledge, the choice of criteria for the very frequent problem of detection of large metallic objects is presented, ways to model mass assignments for each of the criteria are illustrated, and frame of discernment as well as subsets to which masses can be assigned by each of these criteria are shown. Furthermore, a way is proposed for including discounting factors that can model influence of environmental conditions, i.e. of a concrete scenario through deminer's confidence in reliability of each of the sensors, relative importance of criteria, as well as confidence of sensors in their assessment when judging about some criterion. After that, first results of discounting and fusion are obtained, that seem to be very promising. Finally, ideas for interpreting the results of fusion are presented, in the sense of serving to a deminer an ordered list of guesses what an object under observation could be, together with three suggested ways for finding confidence degrees. Our belief is that these masses will become even more realistic and results even more useful once the trials are done, from which it should be possible to pool these preliminary models of masses as well as of discounting factors.

Based on this preliminary work, future work aims at investigating ways to generalize this model to other cases, further analyzing ways to add discounting factors, and testing ways to modify the model by allowing the possibility that sensors do not refer to the same object.

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